CENG 4480

Embedded System Development & Applications

Lec 05: Sparse Conv

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Overview

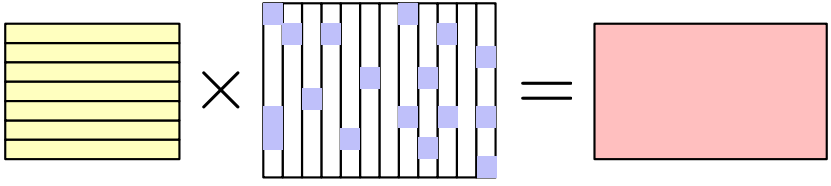
1. Kernel Sparse Convolution
2. Submanifold Sparse Convolution

Overview

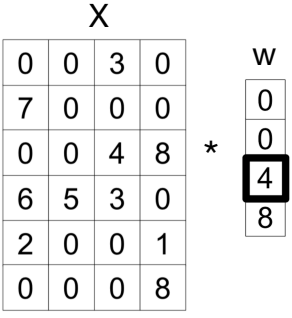
Kernel Sparse Convolution

Sparse Convolution

- Our DNN may be redundant, and sometimes the filters may be sparse
- Sparsity can be helpful to overcome over-fitting



Sparse Convolution: Naive Implementation 1



Algorithm Sparse Convlution Naive 1

1: **for all** w[i] **do**
2: **if** w[i] = 0 **then**
3: Continue;
4: **end if**
5: output feature map $\boldsymbol{Y} \leftarrow \boldsymbol{X} \times w$[i];
6: **end for**

Sparse Convolution: Naive Implementation 1

X

0	0	3	0
7	0	0	0
0	0	4	8
6	5	3	0
2	0	0	1
0	0	0	8

*

w

0
0
4
8

Algorithm Sparse Convlution Naive 1

1: **for all** w[i] **do**
2: **if** w[i] = 0 **then**
3: Continue;
4: **end if**
5: output feature map $\boldsymbol{Y} \leftarrow \boldsymbol{X} \times w$[i];
6: **end for**

BAD implementation for Pipeline!

Instr. No.	Pipeline Stage						
1	IF	ID	EX	MEM	WB		
2		IF	ID	EX	MEM	WB	
3			IF	ID	EX	MEM	WB
4				IF	ID	EX	MEM
5					IF	ID	EX
Clock Cycle	1	2	3	4	5	6	7

Sparse Matrix Representation

A

0	0	3	0
7	0	0	0
0	0	4	8
6	5	3	0
2	0	0	1
0	0	0	8

A matrix example

rowptr

- row0 (3,2)
- row1 (7,0)
- row2 (4,2), (8,3)
- row3 (6,0), (5,1), (3,2)
- row4 (2,0), (1,3)
- row5 (8,3)

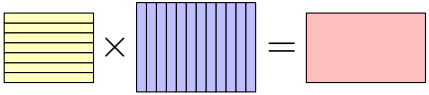
Compressed Sparse Row (CSR)

colptr

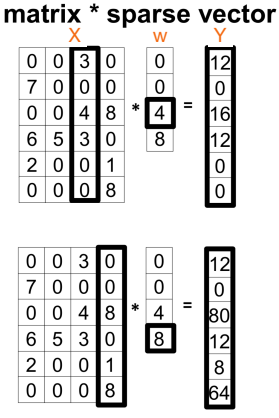
- col0 (7,1), (6,3), (2,4)
- col1 (5,3)
- col2 (3,0), (4,2), (3,3)
- col3 (8,2), (1,4), (8,5)

Compressed Sparse Column (CSC)

- CSR: Good for operation on feature maps
- CSC: Good for operation on filters
- We have better control on filters, thus usually CSC.



Sparse Convolution: Naive Implementation 2



- BAD implementation for Spatial Locality!
- Poor memory access patterns

SOTA 2: Sparse Convolution

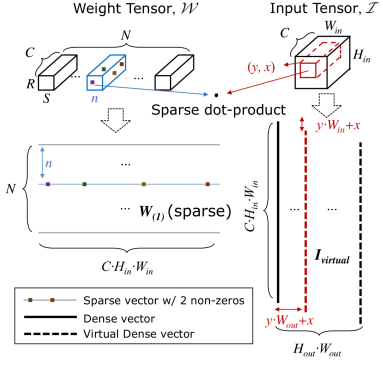


Figure 1: Conceptual view of the direct sparse convolution algorithm. Computation of output value at (y,x)th position of nth output channel is highlighted.

```
for each output channel n {
 for j in [W.rowptr[n], W.rowptr[n+1]) {
  off = W.colidx[j]; coeff = W.value[j]
  for (int y = 0; y < H_OUT; ++y) {
   for (int x = 0; x < W_OUT; ++x) {
    out[n][y][x] += coeff*in[off+f(0,y,x)]
   }
  }
 }
}
```

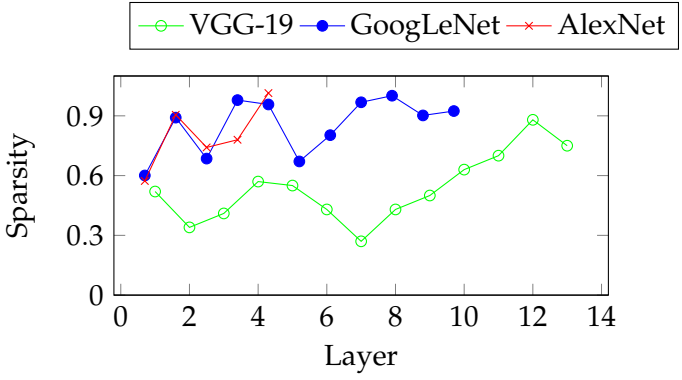
Figure 2: Sparse convolution pseudo code. Matrix **W** has *compressed sparse row* (CSR) format, where `rowptr[n]` points to the first non-zero weight of nth output channel. For the jth non-zero weight at (n,c,r,s), `W.colidx[j]` contains the offset to (c,r,s)th element of tensor `in`, which is pre-computed by layout function as $f(c,r,s)$. If `in` has CHW format, $f(c,r,s) = (cH_{in}+r)W_{in}+s$. The "virtual" dense matrix is formed on-the-fly by shifting `in` by $(0,y,x)$.

1

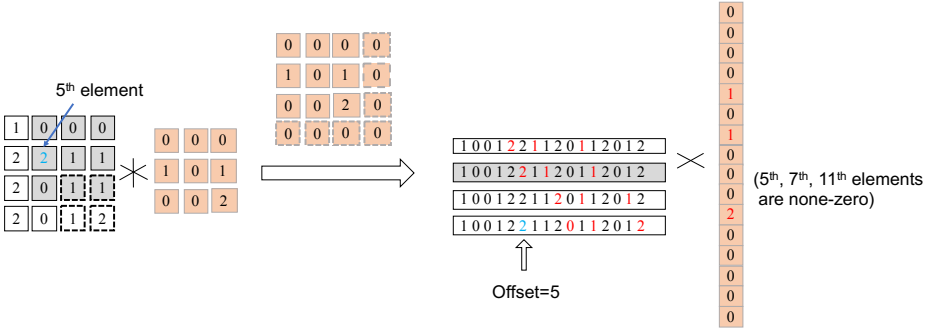
[1] Jongsoo Park et al. (2017). "Faster CNNs with direct sparse convolutions and guided pruning". In: *Proc. ICLR*.

Discussion: Sparse-Sparse Convolution

- Sparsity is a desired property for computation acceleration. (`cuSPARSE` library, direct sparse convolution, etc.)
- Sometimes not only the filters but also the input feature maps are sparse.



Discussion: Sparse-Sparse Convolution



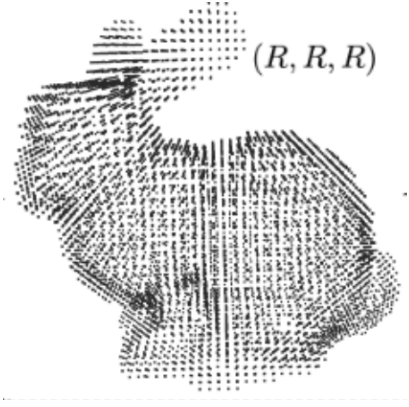
- Efficient programming implementation required; (Improve pipeline efficiency)
- When sparsity$(input) = 0.9$, sparsity$(weight) = 0.8$, more than $10\times$ speedup;
- Some other issues:
  - How to be compatible with pooling layer?
  - Transform between dense & sparse formats

Overview

Submanifold Sparse Convolution

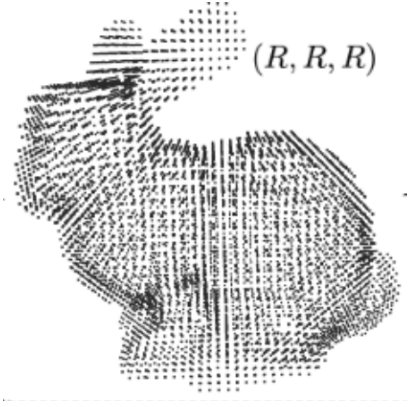
Voxel Data

In real world, we have to handle voxel data sometimes. For example, in point cloud analysis, 3D voxel data is widely used. A simple example is shown here and it can be viewed as $V \in (1, R, R, R)$.



Voxel Data

Here is a rabbit with shape $V \in (1, 64, 64, 64)$. If using traditional convolution to extract its feature, the GPU will out of memory very soon because the input $V \in (1, 64, 64, 64)$ can be viewed as an image $I \in (1, 4096, 64)$.

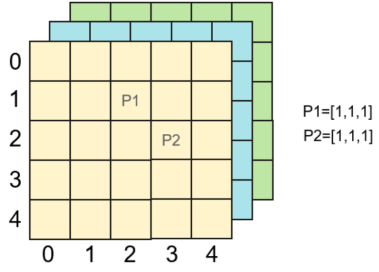


Submanifold Sparse Convolution

To overcome this issue, we use 3D sparse convolution for voxel data analysis. Sparse convolution only calculate the data points where voxel data exists.

Submanifold Sparse Convolution

In this Lab, we are going to build a sparse convolution from scratch. Here we use the example input:



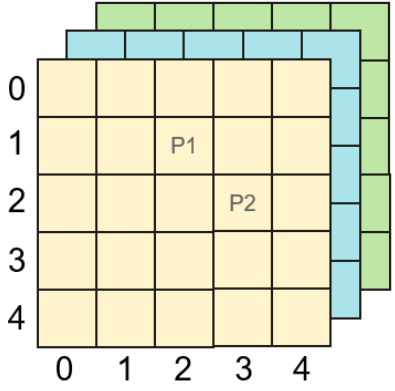
where P1 and P2 has pixel value of 1 in 3 channels.

Firstly, we build a hash table to store the input data. Considering the following case:

conv2D(kernel_size=3, out_channels=2, stride=1, padding=0)

Submanifold Sparse Convolution

We can build an input table H_{in} like this:

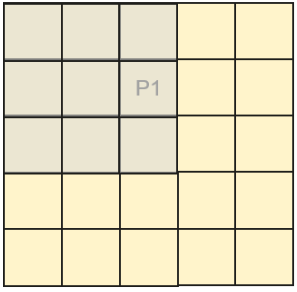


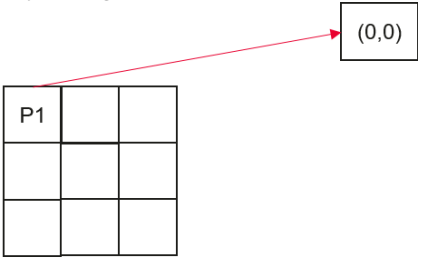
P1=[1,1,1]
P2=[1,1,1]

H_in

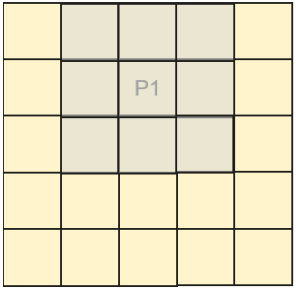
0	(2,1)
1	(3,2)

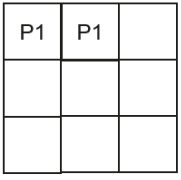
Then we build an output hash table. Firstly, we generate a P_{out} table as follow:





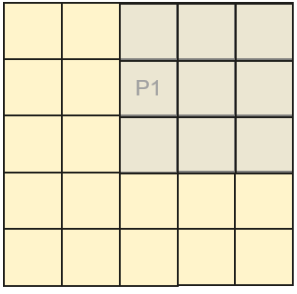
Then we build an output hash table. Firstly, we generate a P_{out} table as follow:





(0,0)
(1,0)

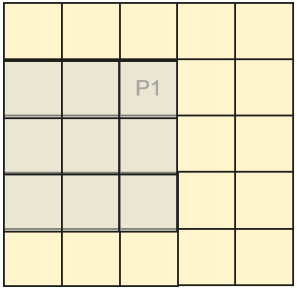
Then we build an output hash table. Firstly, we generate a P_{out} table as follow:



P1	P1	P1

(0,0)
(1,0)
(2,0)

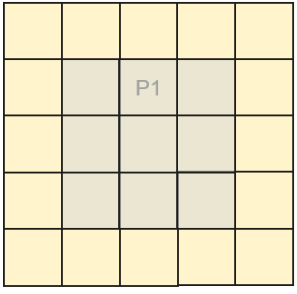
Then we build an output hash table. Firstly, we generate a P_{out} table as follow:



P1	P1	P1
P1		

(0,0)
(1,0)
(2,0)
(0,1)

Then we build an output hash table. Firstly, we generate a P_{out} table as follow:

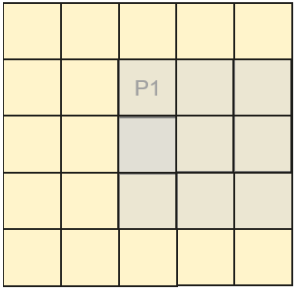


P1	P1	P1
P1	P1	

(0,0)
(1,0)
(2,0)
(0,1)
(1,1)

Submanifold Sparse Convolution

Then we build an output hash table. Firstly, we generate a P_{out} table as follow:

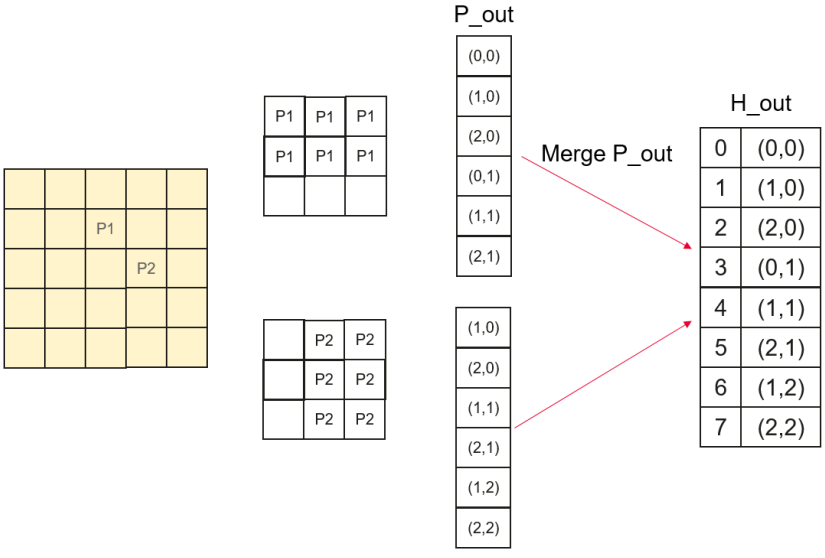


P1	P1	P1
P1	P1	P1

(0,0)
(1,0)
(2,0)
(0,1)
(1,1)
(2,1)

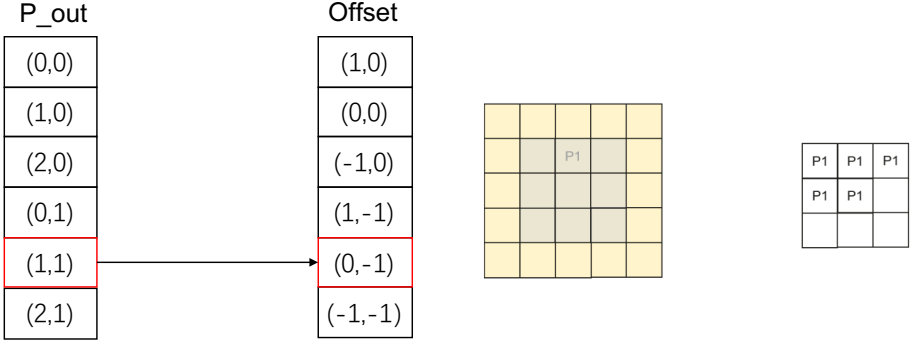
Submanifold Sparse Convolution

After applying the same process to P_2, we get an output hash table H_{out} via P_{out} mergi



Submanifold Sparse Convolution

- Next we build up a Rulebook to realize H_{in} to H_{out}.
- To build the rule book, we have to build an offset map like this:

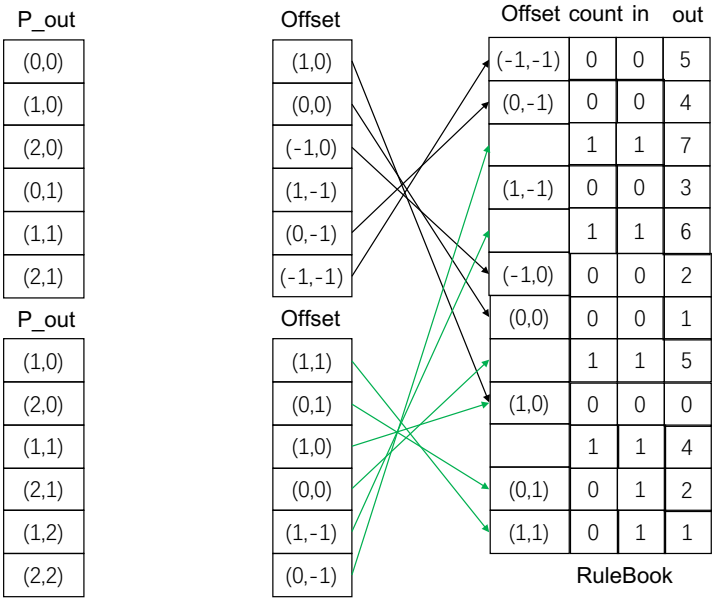


Quick Question:

Please write the offset map of $P2$ by yourself.

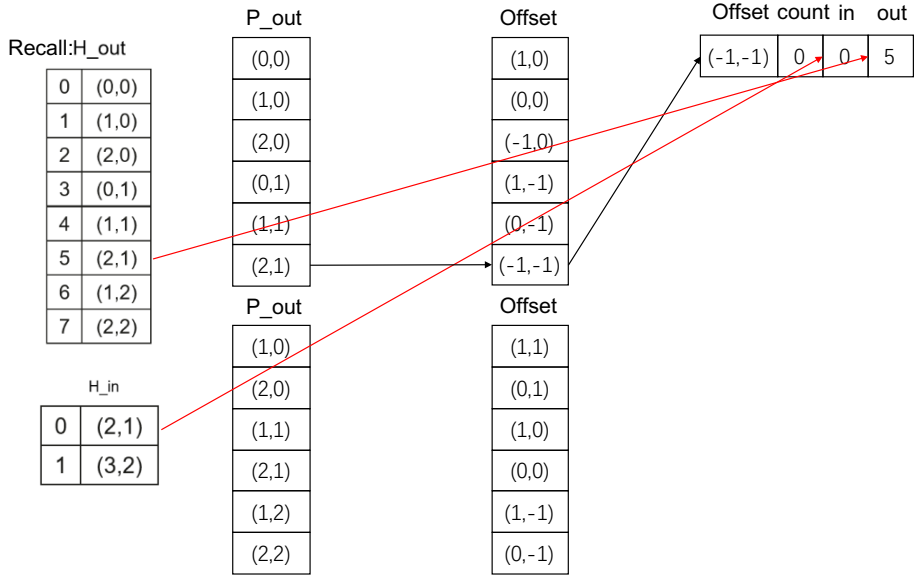
Submanifold Sparse Convolution

After obtaining the offset map, we can finally build up the rule book as follow:



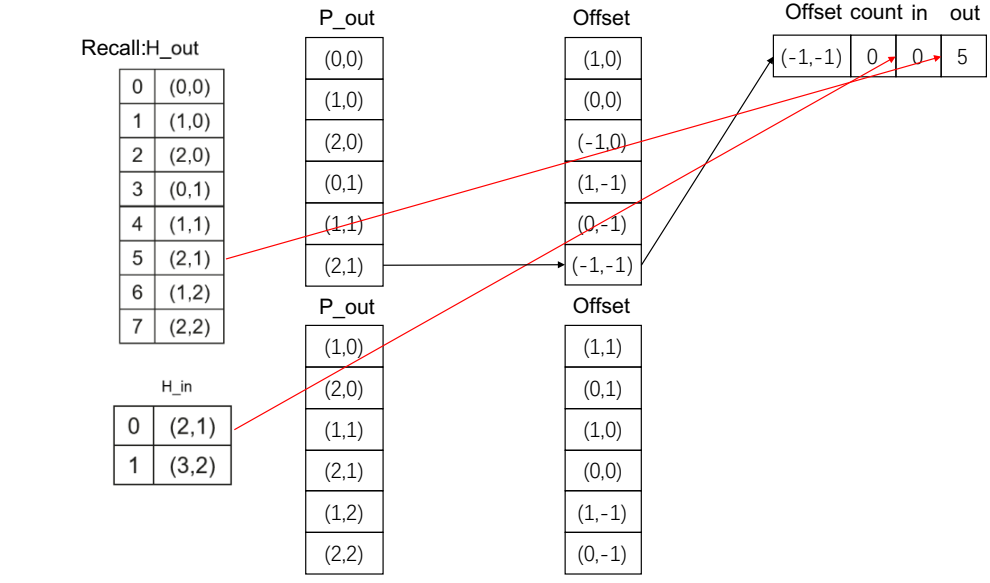
Submanifold Sparse Convolution

Recalling the H_{in} and H_{out}, the rulebook is generated as follow:



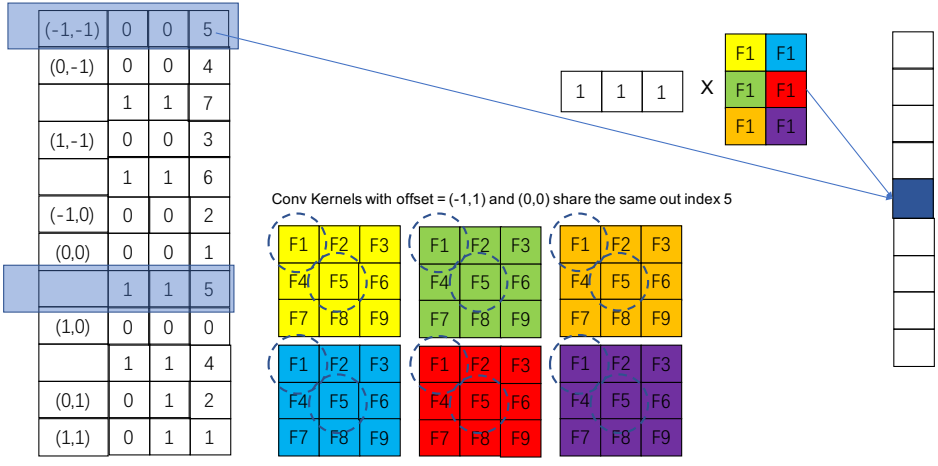
Submanifold Sparse Convolution

If the offset already exists, we simply add 1 in count:



Submanifold Sparse Convolution

After getting rulebook, we can apply sparse convolution:



For P_1, the reults is shown above, which is the blue points in 5-th row. Please practice P_2 by yourself